Simulation of Adaptive Noise Canceller for an ECG signal Analysis

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***Abstract*— In numerous applications of signal processing, communications and biomedical we are faced with the necessity to remove noise and distortion from the signals. Adaptive filtering is one of the most important areas in digital signal processing to remove background noise and distortion. In last few years various adaptive algorithms are developed for noise cancellation. In this paper we have presented an implementation of LMS (Least Mean Square), NLMS (Normalized Least Mean Square) and RLS (Recursive Least Square) algorithms on MATLAB platform with the intention to compare their performance in noise cancellation application. We simulate the adaptive filter in MATLAB with a noisy ECG signal and analyze the performance of algorithms in terms of MSE (Mean Squared Error), SNR Improvement, computational complexity and stability. The obtained results shows that, the RLS algorithm eliminates more noise from noisy ECG signal and has the best performance but at the cost of large computational complexity and higher memory requirements.**

***Index Terms*— Adaptive filters, LMS, Mean Squared Error (MSE), RLS**

I. Introduction

An adaptive filter has the property of self-modifying its frequency response to change the behavior in time, allowing the filter to adapt the response to the input signal characteristics change. Due to this capability, the overall performance and the construction flexibility, the adaptive filters have been employed in many different applications, some of the most important are: telephonic echo cancellation, radar signal processing, navigation systems, communications channel equalization and biomedical signals processing [1-3].The most common adaptive filters, which are used during the adaption process, are the finite impulse response (FIR) types.

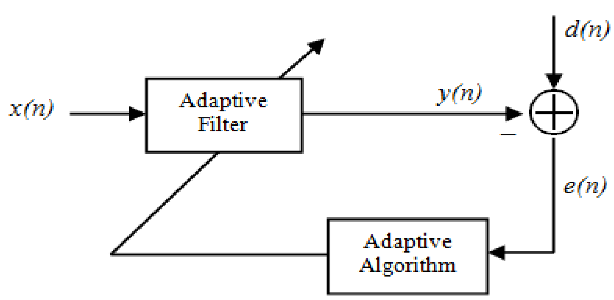

Figure 1. General Adaptive filter configuration

These are preferable because they are stable, and no special adjustments are needed for their implementation.Fig.1 illustrates the general configuration for an Adaptive filter [4]. The adaptive filter has two inputs: the primary input *d(n)*, which represents the desired signal corrupted with undesired noise, and the reference signal *x(n)*, which is the undesired noise to be filtered out of the system.

The goal of adaptive filtering systems is to reduce the noise portion, and to obtain the uncorrupted desired signal. In order to achieve this task, a reference of the noise signal is needed. That reference is fed to the system, and it is called a reference signal *x(n)*. However, the reference signal is typically not the same signal as the noise portion of the primary signal - it can vary in amplitude, phase or time delay. Therefore the reference signal cannot be simply subtracted from the primary signal to obtain the desired portion at the output.

The basic idea for the adaptive filter is to predict the amount of noise in the primary signal, and then subtract that noise from it. The prediction is based on filtering the reference signal *x(n)*, which contains a solid reference of the noise present in the primary signal. The noise in the reference signal is filtered to compensate for the amplitude, phase and time delay, and then subtracted from the primary signal. This filtered noise is the system's prediction of the noise portion of the primary signal, *y(n)*. The resulting signal is called error signal *e(n)*, and it presents the output of the system. Ideally, the resulting error signal would be only the desired portion of the primary signal.

In this work we investigate the performance of various adaptive algorithms with the help of MATLAB simulation [7] and tested for an ECG signal. The paper is organized in four sections; section 2 gives an idea of adaptive algorithms, in section 3 an Adaptive Noise Cancellation (ANC) model is designed and finally the results are discussed in section 4.

II. Adaptive Algorithms

A. Least Mean Square Algorithm

The LMS algorithm [4], is a type of adaptive filter algorithm that is also known as stochastic gradient-based algorithm as it utilizes the gradient vector of the filter tap weights to converge on the optimal wiener solution. With each iteration of the LMS algorithm, the filter tap weights of the adaptive filter are updated according to the following formula:

$$w(n+1) = w(n) + 2\mu e(n)x(n) \tag{1}$$

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Here *x(n)* is the input vector of time delayed input values,

$$x(n) = [x(n)x(n-1)x(n-2)\ldots x(n-N+1)]^T \qquad (2)$$

The vector $w(n) = [w_0(n)w_1(n)w_2(n)\ldots.w_{N-1}(n)]^T$ represents the coefficients of the adaptive FIR filter tap weight vector at time *n*.

The parameter μ is known as the step size parameter and is a small positive constant. This step size parameter controls the influence of the updating factor. Selection of a suitable value for μ is imperative to the performance of the LMS algorithm, if the value is too small the time the adaptive filter takes to converge on the optimal solution will be too long; if μ is too large the adaptive filter becomes unstable and its output diverges.

B. Normalized Least Mean Squared Algorithm

In the standard LMS algorithm, when the convergence factor *μ* is large, the algorithm experiences a gradient noise amplification problem. In order to solve this difficulty, we can use the NLMS (Normalized Least Mean Square) algorithm. The correction applied to the weight vector *w(n)* at iteration *n+1* is "normalized" with respect to the squared Euclidian norm of the input vector *x(n)* at iteration *n*.

We may view the NLMS algorithm as a time-varying step-size algorithm, calculating the convergence factor *μ* as in Eq. (3)[5].

$$\mu(n) = \frac{\alpha}{c + \|x(n)\|^2} \qquad (3)$$

Where: α is the NLMS adaption constant, which optimize the convergence rate of the algorithm and should satisfy the condition 0< α<2, and *c* is the constant term for normalization and is always less than 1.

In NLMS algorithm, the filter weights are updated by the Eq. (4).

$$w(n+1) = w(n) + \frac{\alpha}{c + \|x(n)\|^2} e(n)x(n) \qquad (4)$$

C. Recursive Least Square Algorithm

The RLS algorithm is known for its excellent performance when working in time varying environments but at the cost of an increased computational complexity and some stability problems. In this algorithm the filter tap weight vector is updated using Eq. (5) [7].

$$w(n) = \bar{w}^T(n-1) + k(n)\bar{e}_{n-1}(n) \qquad (5)$$

Eq. (6) and (7) are intermediate gain vector used to compute tap weights.

$$k(n) = u(n)/(\lambda + x^T(n)u(n)) \qquad (6)$$
$$u(n) = w_{\lambda}^{-1}(n-1)x(n) \qquad (7)$$

Where: λ is a small positive constant very close to, but smaller than 1.

The filter output is calculated using the filter tap weights of previous iteration and the current input vector as in Eq. (8).

$$\bar{y}_{n-1}(n) = \bar{w}^T(n-1)x(n) \qquad (8)$$
$$\bar{e}_{n-1}(n) = d(n) - \bar{y}_{n-1}(n) \qquad (9)$$

In the RLS algorithm the estimate of previous samples of output signal, error signal and filter weight is required that leads to higher memory requirements.

III. Adaptive Noise Cancellation

Adaptive noise cancellation (ANC) is performed by subtracting noise from a received signal, and an operation controlled in an adaptive manner is done during the adaptation process to get an improved signal-to-noise ratio. Noise subtraction from a received signal could generate disastrous results by causing an increase in the average power of the output noise. However when filtering and subtraction are controlled by an adaptive process, it is possible to achieve a superior system performance compared to direct filtering of the received signal. Fig.2 shows adaptive noise canceling system.

The ANC system composed of two separate inputs, a primary input or ECG signal source which is shown as *s*(n) and a reference input that is the noise input shown as *x(n)*. The primary signal is corrupted by noise $x_1(n)$. The signal $x_1(n)$ is highly correlated with noise signal or reference signal *x(n)*. Desired signal *d*(*n*) results from addition of primary signal *s*(*n*) and correlated noise signal $x_1(n)$. The reference signal *x(n)* is fed into adaptive filter and its output *y*(n) is subtracted from desired signal *d*(n). Output of the summer block is then fed back to adaptive filter to update filter coefficients. This process is run recursively to obtain the noise free signal which is supposed to be the same or very similar to primary signal *s*(*n*).

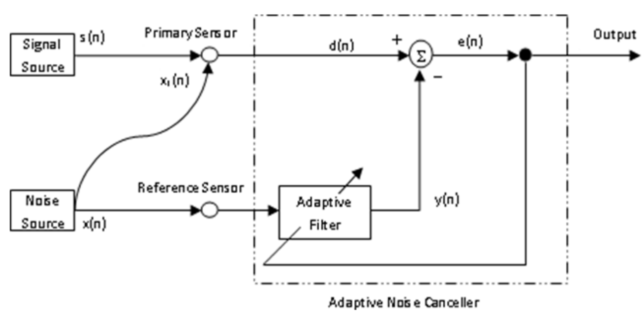

Figure 2. Adaptive Noise Cancellation system

IV. Simulation Results

The adaptive noise canceller was implemented in MATLAB for three algorithms; LMS, NLMS and RLS [7]. In the simulation the reference input signal *x(n)* was a white Gaussian noise of power 1-dB generated using *randn* function in MATLAB, and source signal *s(n)* was a clean amplified ECG signal recorded with 12-lead configuration [6], the desired signal *d(n)* ,obtained by adding a delayed version of *x(n)* into clean signal *s(n)*, $d(n) = s(n) + x_1(n)$ as shown in Fig.3.

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The simulation of the LMS, NLMS and RLS algorithms was carried out with the following specifications:
Filter order N=19, step size μ= 0.009 and iterations= 1000, c= 0.001

The LMS filtered output is shown in Fig.4 (a), the mean squared error generated as per adaption of filter parameters is shown in Fig.4 (b). The step size μ control the performance of the algorithm, if μ is too large the convergence speed is fast but filtering is not proper, if μ is too small the filter gives slow response, hence the selection of proper value of step-size for specific application is prominent to get good results. Fig.5 and Fig.6 shows the output results for NLMS and RLS algorithms respectively. If we investigate the filtered output of all algorithms, LMS adopt the approximate correct output in 750 samples, NLMS adopt in 600 samples and RLS adopt in 250 samples. This shows that RLS has fast learning rate. In Table-I performance analysis of all three algorithms is presented in term of Mean Squared Error (MSE), computational complexity and stability. It is clear from the Table-I, the computational complexity and stability problems increases in an algorithm as we try to reduce the mean squared error.

TABLE I. PERFORMANCE COMPARISON OF ADAPTIVE ALGORITHMS

S.N.	Algorithm	MSE	Complexity	Stability
1.	LMS	1.5×10^{-2}	2N+1	Highly Stable
2.	NLMS	9.0×10^{-3}	3N+1	Stable
3.	RLS	6.2×10^{-3}	$4N^2$	Less Stable

In Table-II SNR Improvement is presented for each algorithm. From Table-I & Table-II it is clear that the RLS algorithm has best performance but same time the computational complexity is also increased. If we investigate NLMS algorithm its performance is comparable with RLS algorithm with slight additional complexity hence NLMS is the favorable choice for most of the industries.

TABLEII. COMPARISON OF SNR IMPROVEMENT

S.N.	Algorithm	SNR Pre	SNR Post	SNR Improved
1.	LMS	0.89	7.04	6.15
2.	NLMS	0.89	9.26	8.37
3.	RLS	0.89	10.87	9.98

CONCLUSIONS

The main objective of this paper was to implement an adaptive noise canceller for de-noising an ECG signal and test the performance of the system for various adaptive algorithms.When input signal is non-stationary in nature, the RLS algorithm proved to have the highest convergence speed, less MSE,and higher SNR Improvement but at the cost of large computational complexity and memory requirement. The NLMS algorithm changes the step-size according to the energy of input signals hence it is suitable for both stationary as well as non-stationary environment and its performance lies between LMS and RLS. Hence it provides a trade-off in convergence speed and computational complexity. The implementation of algorithms was successfully achieved, with results that have a really good response.

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Figure. 3(a) Clean ECG signal s(n);(b) Noise signal x(n);(c) desired signal d(n)

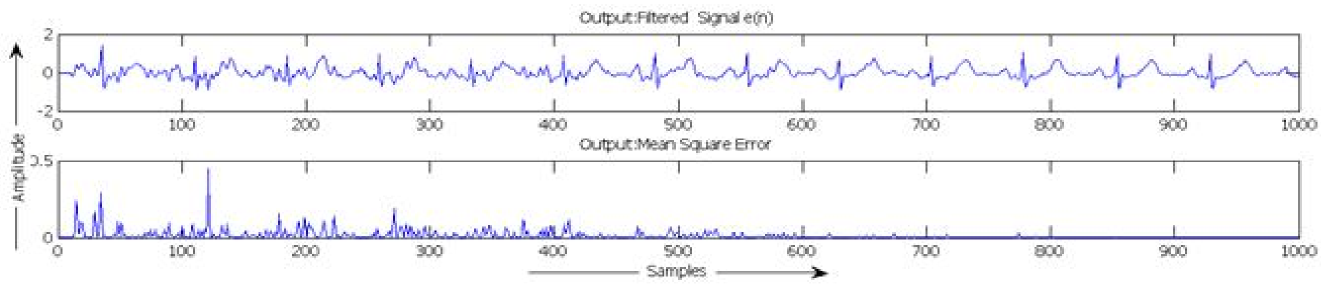

Figure 4. MATLAB simulation for LMS algorithm; N=19, step size=0.009

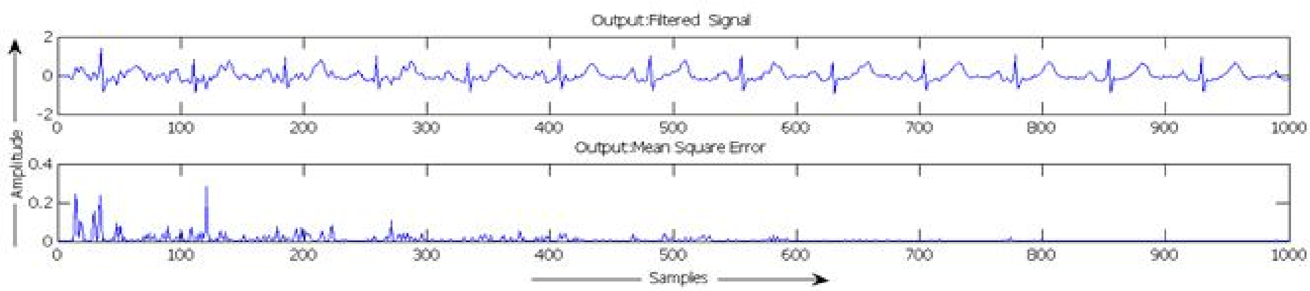

Figure 5. MATLAB simulation for NLMS algorithm; N=19, step size=0.001

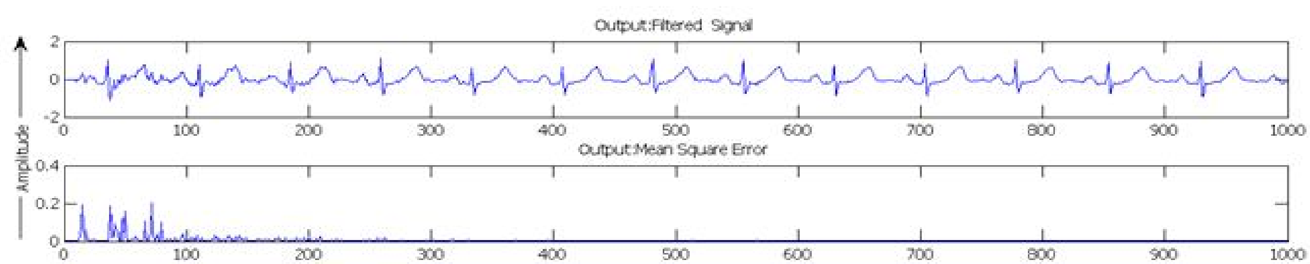

Figure 6. MATLAB simulation for RLS algorithm; N=19, λ=1

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